Enhancing Electricity Consumption Forecasting using Hybrid ANN-ANFIS Models for Smart Grid Applications

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(Received January 31, 2025; Revised July 06, 2025; Accepted August 20, 2025)

Abstract: Forecasting electricity consumption is a critical task for efficient energy management and for the integration of renewables. The present work uses a combination of two state-of- art techniques, Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference System (ANFIS), to produce more accurate predictions. We develop and compare several forecasting models using four years of data from an institute which employs solar, diesel generator and hydel power. The results reveal that ANFIS does better than ANN with lower Mean Absolute Percentage Error and Mean Squared Percentage Error. The research paper showed that ensemble methods boost electricity consumption prediction outcomes, and they can be by utility companies in their smart grid applications. This research is an effort to make a step forward in data-driven forecasting to meet the growing demand for energy in a sustainable manner and by applying machine learning methods which should maintain data forecasting as needed in planning efforts.

Keywords: ANFIS; Artificial Neural Networks; Electricity Forecasting; Machine Learning for Energy Management.; Renewable Energy Integration; Smart Grid Prediction

1. Introduction

Electricity consumption forecast has become more significant in present-day energy the board frameworks as request side administration and asset designation depend on exact expectations. A few traditional statistical approaches neglect the effect of energy utilization designs on climate, economic indicators, and client conduct. Because of their ability to demonstrate nonlinear collaborations and catch convoluted transient conditions, AI strategies, especially neural networks, have arisen as viable instruments for time series estimating. This exploration sets out to work on the accuracy and dependability of power utilization Figures by utilizing the force of neural networks and researching innovative troupe procedures tweaked to the space's special qualities.

Over the last decade, there has been a blast in research endeavours committed to assessing power use utilizing different AI calculations, most outstandingly neural networks. These models have an unprecedented ability to distinguish stowed-away examples and adjust to changing shopper elements. Nonetheless, an exploration hole exists, requiring more assessment of the potential outcomes of group approaches custom-made explicitly for determining power utilization. While single-brain network models definitely stand out enough to be noticed, utilizing the benefits of gathering draws near, which coordinate many models to construct a more powerful and precise determining framework, has been somewhat underutilized in this unique situation. By defeating this hole, this study expects to work on the exactness of power utilization projections. The methodology utilized in this study depends on foreseeing power use by utilizing the adaptability of neural networks. The dataset utilized incorporates authentic utilization information from the Hindustan College of Science and Technology, Mathura Camus. To set up the dataset for demonstrating highlight scaling methods are thoroughly built. The examination of troupe techniques that consolidate a few brain network geographies and information designs is a basic piece of this review.

The study delves into the application of Neural Network (NN) and ANFIS methodologies to leverage architectural diversity for enhancing the predictive capabilities of neural network ensembles. Its primary aim is to assess the

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potential superiority of ensemble methods over individual neural network models in forecasting electricity consumption. Through meticulous experimental design and comprehensive analysis, this research endeavours to pave the way for more accurate and robust energy predictions.

Machine Learning techniques, either traditional ones or neural networks-based approaches have been used in recent years, yielding hopeful outcomes in electricity usage prediction. In this research paper, we have introduced a neural network-based approach and ANFIS based approach to predict electricity consumption.

2. Literature Review

Precise prediction of power usage is paramount for ensuring efficient energy management and fostering sustainability. To optimize efficiency and reduce operational expenses, energy planners, grid operators, and regulators rely on precise consumption forecasts. Anticipating periods of high demand enables organizations to mitigate potential energy shortages through proactive measures like load shedding or peak shaving. Moreover, accurate consumption projections facilitate the seamless amalgamation of renewable energy resources into the grid, as fluctuations in demand can be pre-emptively balanced.

In the context of addressing consumption prediction challenges, the contrast between conventional statistical techniques such as Auto Regressive Integrated Moving Average (ARIMA), exponential smoothing, and regression, and neural networks highlights the evolving landscape of predictive modelling for electricity consumption.

ARIMA models are one of the approaches to forecast electricity use that can reflect the features of seasonal, nonlinear, and dependence on the time-series data. It performs statistical testing for accuracy verification and fine-tunes parameters for enhanced predictive accuracy in low energy data aggregation[1)].

Using a model for time series that have been shown to produce larger quality and accuracy of prediction for industrial electricity consumption than other statistical methods, ARIMA (0,1,1) was the best demonstrating approach for industrial electricity consumption in Nigeria[2)].

The ARIMA method models the trend component in electricity consumption forecasting and represents linear characteristics well. It has, however, weakness in predicting nonlinear components, therefore a hybrid model comprising ARIMA and deep learning methods is therefore needed for better accuracy[3)].

Utilizing the ARIMA (11,1,12) model, this study reveals that December 2021 peak electricity consumption in Luzon will be at 10,497.65 MW, with values in the following years increasing, which serves as a basis for allocation of resources and infrastructure planning in the energy industry[4)].

ARIMA forecasting model for predicting future electricity demand is depicted by this study[5)], indicating its applicability to electricity consumption forecasting owing to lowest values of training and testing error compared to other models.

This paper[6)] presents how this approach of ARIMA can be used as a forecasting tool to forecast the hourly electricity consumption in the coal washing plants by taking data from January 2011 to end of February 2013 to improve the efficiency of electrical energy consumed in SCADA systems to improve operational performance.

An ARIMA model is developed to predict electricity demand using the means of data to fill the outliers, making the dataset stationary and applying grey system correction with a view to obtaining a more accurate prediction of seasonal electricity demand over a six-month period from the 1st January 2022 to 31st March 2023[7)].

This study[8)] suggests ARIMA models of electricity consumption using ACF and PACF plots to recognize values of (p, d, q). In the end, the model was able to make predictions with 4.332%or around 4.4%MAPE value.

Conventional methods, albeit essential, often fall short of encompassing the intricate nonlinear relations and nonlinear dynamics present in consumption datasets. ARIMA and exponential smoothing approaches based on linear assumptions that can be challenging to reconcile with changing consumption due to multiple other variables. With assumptions of linearity and independence among factors, regression models are under heavy backlash.

On the other hand, neural network architectures allow for a flexible approach to model nonlinear trends, time dependencies, and interactions between many variable[9),10)]. They can comprehend complex patterns and change in location, which helps to address the variety of power use and provide more detailed and adaptable predictions. In contrast, this trend has moved into more of a machine learning based approaches such as neural networks, which are mature enough to provide stable solutions to predict power consumption outside the limits of traditional methods.

It indicates that Multilayer Perceptron (MLP) neural networks manage to forecast short-term with higher performance than polynomial regression methods[11)]. Since they can learn complicated patterns, and they have high power for parsing big data, they are an excellent option to provide accurate forecasting of the future.

This paper proposes the improved BP neural network algorithm for predicting the electricity consumption based on the established prediction lead time model[12)]. This is very suitable for short-term energy consumption prediction as it increases the speed and fidelity of prediction.

This paper proposes two neural network-based approaches for forecasting electric consumption using the recurrent neural network (RNN) and LSTM model. And the LSTM is a big upgrade over the RNN. It gets a very high R^2 score of 90% and lower error rates[13].

This work highlights the significant issues of increase in energy demand and the amalgamation of renewable energy resources (RERs) into smart houses with the aid of a real-time pricing-based demand response program. The study demonstrates that utilizing an amalgam forecasting model (CNN-LSTM) for short-term solar PV generation can improve appliance scheduling in New Delhi, achieving 53.5% lower electricity costs with a payback period of 5.112 years for the PV panel[14, 15].

In this paper[16], authors present a new method for forecasting electricity consumption utilizing graph-based models (General Framework), such as Graph Convolutional Networks (GCN) and Graph SAGE, that provide improved performance and explainability of forecasts by capturing the spatial distribution and underlying relational intricacies of decentralized networks.

The paper compares three ML methods for predicting electricity consumption, namely: a Radial Basis Function network, a feedforward Neural Network and a Recurrent Neural Network, showing that the RBF method yields the best results, accurately predicting daily electricity consumption in Tirana, Albania[17].

We formulate a neural network-based approach in hierarchical electricity consumption forecasting with the necessary characteristics of hierarchical structure including both levels of hierarchy and granularity[18]. It shows that deeper hierarchical understanding models (DHUs) outperform classical models when it comes to the FCF, which in turn increases the forecasting accuracy by reporting the computational efficiency trade-offs.

Accurate Estimation of electricity demand has a great significance in the smart-grid response management[19]. It compares several advanced ANN architectures with traditional statistical models and shows better prediction accuracy.

There is a growing need for algorithms or machine learning based models that process the input parameters through various ways which not only increase yield but also crop selection, for prediction of suitable crops to grow on agriculture fields, which is proposed is this study[20]. This tool also compares various machine learning algorithms in terms of accuracy under various training/testing ratios.

Using a multilayer perceptron artificial neural network model, the study forecasts India electricity consumption to increase by 50% reaching over 1800 TWh by 2030. We proposed this method that combines the canonical cointegrating regressions, ANN for time series[21].

This paper[22] addressed the problem of forecasting electricity consumption in industrial enterprises using ANN methods where Long-Short Term Memory was proposed as an effective way to predict electricity consumption because of its power of adaptability to the surrounding environment and learning the time series data trend from records of prior time to achieve better energy efficiency and cost economy.

Ten machine learning models were fine-tuned to forecast short-term wind speed and assessed against each other based on RMSE, MAE, correlation and runtime. Overall, RF and gradient-boosted trees were the better performing models, with GBT also allowing a shorter training time, helping interest in more efficient wind prediction approaches for power systems[23].

This study[24] offers a neural network model for predicting monthly electricity usage based on an enriched data set with several computed features. With a prediction error of around 5%, the model was successful in increasing the control over electricity consumption and facilitates production planning.

Although neural networks have demonstrated great promise in predicting energy consumption, there remains research void in investigating more sophisticated ensemble approaches designed for this area[25]. While individual neural network models can produce excellent forecasts, merging many models using ensemble approaches should improve prediction reliability and resilience even more.

In a way, ANFIS has become an efficient tool to estimate energy use through the combined benefits of synaptic networks and Fuzzy Logic[26]. ANFIS models complex, non-linear interactions inherent in energy consumption patterns by combining the flexibility of neural networks in learning from data with the linguistic expressiveness of fuzzy logic[27]. As energy demands change due to factors such as technological advancements, societal changes, and environmental concerns, the use of ANFIS holds promise in providing precise predictions that contribute to effective resource allocation, load balancing, and long-term energy management. In this context, this study digs into the use of ANFIS for energy consumption forecasting, intending to uncover its potential, methodology, and consequences in this vital subject.

This research[28] proposes an amalgam model named GA–ANFIS–FCM, composed of fuzzy c-means clustered ANFIS and genetic algorithm reaching an accurate result of the mean absolute percentage error of 7.6345, which proves 92.4% in accuracy of predicting electricity use in Lagos districts, Nigeria.

In this study, we assess the performance of coconut oil as a phase change material for thermal energy storage (TES) in tropical houses, and its ability to maintain stable indoor conditions, whilst decreasing cooling energy. An ANN is used to predict energy consumption using parameters including outdoor temperature and humidity[29].

This work describes a new hybrid model created on ANFIS model for electrical consumption forecasting[30]. The Firefly Algorithm (FA) is used to optimize ANFIS for

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improved accuracy, demonstrating reduced RMSE error and MAPE between ANFIS forecasts and 24-year historical data from smart meters in Cameroon.
This research applied the ANFIS to predict the power use for seven different nations[31]. It then compared ANFIS with other models and reviewed the valuation of performance via error metrics. The accuracy of ANFIS was found to differ between countries and forecasting periods.
An ANFIS was developed and used to prediction the very-short term electricity consumption for an educational building, demonstrating high precision with correlation coefficients of 0.98017 for training and 0.9778 for testing at 30-minute forecasts[32].
The paper[33] proposed a machine learning model based on ANFIS for electricity consumption forecasting as described in paper. Employs inputs of errors from previous iterations, Category-Based Prediction, for improved speed of convergence as well as output accuracy and utilizes discrete wavelet transform for better filtering and lower percentage error in forecasting
This paper[34] shows that even though a neural network works perfectly at predicting the Ghanaian electrical consumption, ANFIS model outperforms traditional techniques such as SVR, LS-SVM and ARIMA, with a sufficiently good and stable parameter settings, high and reliable accuracy can be achieved with high but realistic and low training data with reduction in forecasting error particularly.
Among the various structures, the ANFIS using Gaussian and Generalized Bell membership functions is shown to be superior in modeling the highly nonlinear hysteresis behavior of the MR damper[35]. From the results, the Gaussian function is approximately 1% more accurate than the Morlet wavelet making it more favorable for future modeling and control system design.

3. Prediction Using Neural Approach

3.1. Dataset Preparation and Splitting

In order to guarantee reproducible training, and model-tuning and evaluation methods, the dataset was split into training and testing set at 80:20. Eighty percentage of the entire data was used for training the models, which was enough to learn of how to consume, while the other twenty percentage was used for testing to impartially evaluate the generalization performance. It was thus used for all energy sources (solar, diesel generator and hydel power) and to ensure the comparability of model outputs.

3.2. Artificial Neural Network

The theory of ANN draws encouragement from biological neural networks found in the human brain, offering a simulated representation of these intricate systems. Within artificial neural networks (ANN), numerous

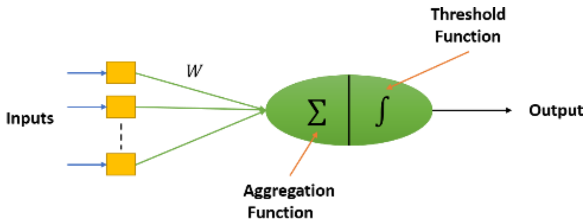

Fig. 1: Conventional Neural Network

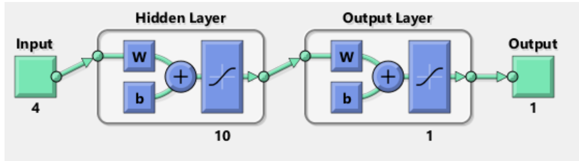

Fig. 2: ANN Network Architecture

interconnected neurons span across different layers, as depicted in Figure 1, featuring feedback loops for adjusting weights. Figure 2 illustrates the network architecture of ANN. In a convolutional neural network, the initial layer comprises input neurons, conveying information to subsequent stages (hidden layers), which then transmit processed data to output neurons in the following layer (output layer). Determining the number of neurons in a hidden layer often involves iterative experimentation. The feedback mechanism plays a crucial role in refining ANN output and minimizing disparities with the desired output. MATLAB's neural network fitting tools were employed to model the ANN. Despite its advantages, ANN possesses limitations such as its dependency on extensive training data and prolonged training durations, especially for complex problems. In the face of challenges arising from the lack of precise understanding of bio-neuronal activities, several neuron architectures, such as union neuron and product neuron have been suggested to deal with the difficulties.
The ANN model structure used in this study was developed through empirical calibration and domain-specific best practices for investment return time series prediction.
We iteratively tested several settings, and finally we selected one hidden layer with 10. This configuration offered the optimal trade-off between the predictive accuracy and the computational complexity. Adding more than 10 neurons only slightly improved the accuracy and did so at the price of additional training time and higher chances for overfitting.
The smooth, nonlinear mapping capabilities of sigmoid activation function employed at the hidden layer is an effective approach to model nonlinear and complex relationships in electricity consumption data. The output activation of linear Feed the continuous consumption values prediction without constraints.
The Levenberg Marquardt backpropagation algorithm was utilized to maximize learning efficiency and minimize error. This algorithm has been proved to have a faster

convergence rate than traditional gradient descent methods, and it has the strengths when it comes to small-large dataset, as we observed in our case.

3.3. Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System is a sort of ANN that combines elements of fuzzy logic and traditional neural networks. Jang introduced it in 1993 to represent the modeling of complicated systems with vagueness and uncertainty.

ANFIS is a Hybrid system which means it uses a Fuzzy inference system to interpret the input data with a neural network to learn and optimize the parameters of the fuzzy system. It has a five-layer architecture: (1) input layer, (2) fuzzy layer, (3) normalization layer, (4) rule layer, and (5) output layer.

Input variables enter the system through the input layer and then pass through a collection of fuzzy sets characterized by membership functions. The output of the fuzzy layer is normalized, and this normalized output is then passed on to the rule layer, where appropriate fuzzy rules are taken, and inputs are mixed. The rule layer output is then inputted to an output layer, which outputs an output value for ANFIS. To optimize ANFIS parameters, a hybrid of the multinomial learning algorithm that combines the gradient and lowest squares methods has been utilized.

The ANFIS model has an architecture, in which each layer has several nodes that take inputs then carry out calculations and send the calculations results to the nodes of the next layer Figure 3. In ANFIS, the hybrid learning algorithm is utilized to tune the parameters of the fuzzy sets and model weights by a combination of gradient descent and backpropagation of errors.

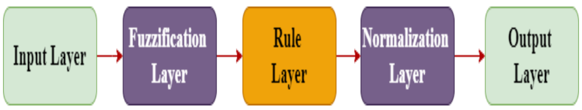

Fig. 3: ANFIS Model

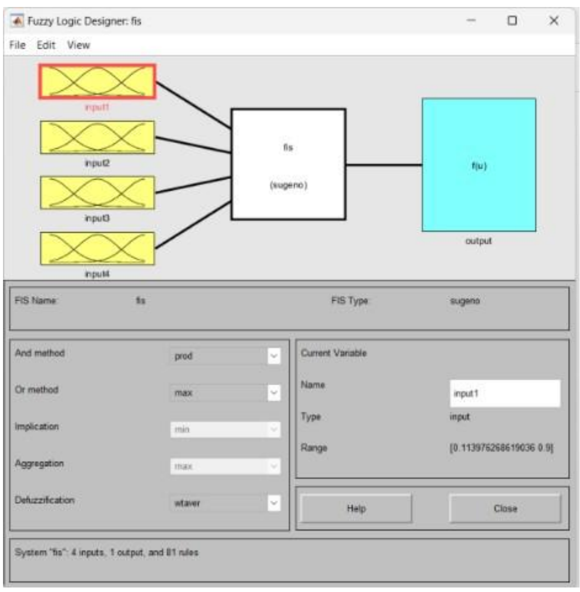

Fig. 4: ANFIS Inputs and Output MATLAB Window

Table 1: Factors Considered for ANFIS

Parameters	Values
FIS Type	Sugeno
And Method	prod
Or Method	Max
Implication Method	prod
Aggregation Method	sum
Defuzzification Method	wtaver
Membership function	triangular
Inputs	1x4 fisvar
Outputs	1x1 fisvar
Rules	1x81fisrule

ANFIS has several advantages over other modeling techniques. It can model non-linear and complex systems with high accuracy and robustness. It can also handle uncertainties and noise in the input data. ANFIS is also computationally efficient and can be trained using small datasets. Table 1 displays the factors of the ANFIS architecture. The ANFIS architecture containing the relation between inputs and output is shown in Figure 4.

4. Electricity Consumption Data

Electricity consumption data is sourced from an 11 kV substation located at Hindustan College of Science and Technology in Farah, Mathura. The dataset encompasses power utilization from various sources including solar systems (405 kW capacity), hydel power (DVVNL, 11KV, 495 KVA), and power generated by diesel generator sets (DG sets, ranging from 500KVA to 1010 KVA), as depicted in Figure 5. Subsequently, this data undergoes analysis and is fed into a neural network for predictive modeling. The neural network architecture consists of three layers namely (a) input layer, (b) hidden layer, and (c) output layer. The input layer accommodates neurons equivalent to the number of inputs, without any processing occurring at this stage. Inputs are then forwarded to the subsequent layer, known as the hidden layer. Finally, the output layer delivers the ultimate predictions.

5. Results

We evaluate the proposed approach on a given dataset. The ANFIS model achieves high accuracy in predicting electricity consumption with a better mean square percentage error and root mean square percentage error. The MAPE and MSPE are calculated using Eq. 1 and Eq. 2. The results of ANN and ANFIS are summarized in terms of MAPE, and MSPE and are given in Table 2 to Table 7. The formula used for calculating mean absolute percentage error (MAPE) and mean square percentage error (MSPE) is given below.

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$$MAPE = \frac{\sum_{j=1}^{n}\left|\frac{E_j}{A_j}\right|}{n} \quad (1)$$

$$MSPE = \frac{\sum_{j=1}^{n}\left(\frac{E_j}{A_j}\right)^2}{n} \quad (2)$$

Where

$$error\ E_j = P_j - A_j$$
$$P_j = predicted\ value, A_j = Actual\ Value$$
$$j = 1, 2, 3, \ldots \ldots \ldots \ldots n$$

We compare the proposed approach with conventional neural networks. The training performance of ANN and ANFIS models for DVVNL data are depicted in Figure 6 and Figure 7 respectively.

Regression plots were integral in verifying that the network prediction was performing well and accurately predicting the outputs. In Figure 8 and Figure 9 the regression analysis plots of ANN and ANFIS during training for DVVNL data.

Unlike the ANN model, all the ANFIS model's predicted values were matched with values during training and testing. Following this, the predictability of the ANFIS model is demonstrated by means of this study.

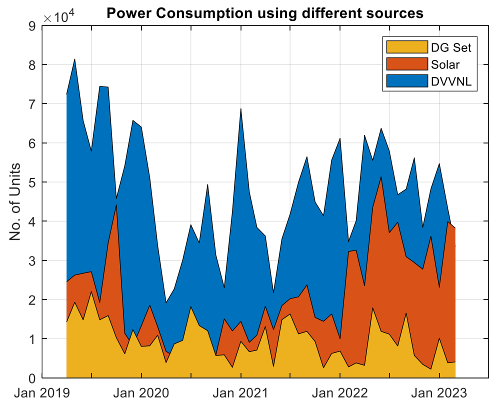

Fig. 5: Collected Data

Fig. 6: Training Performance of ANN for DVVNL data

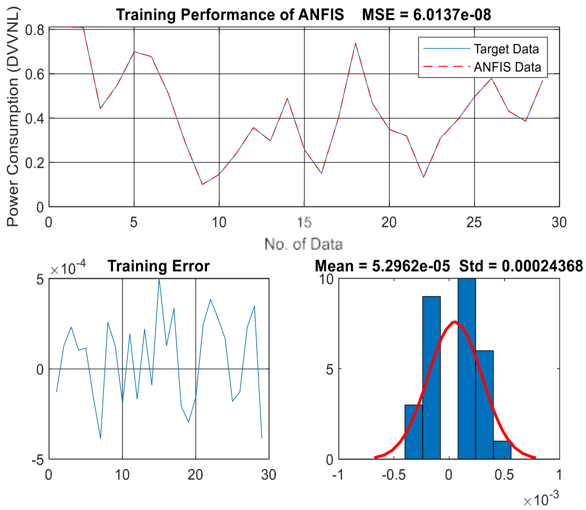

Fig. 7: Training Performance of ANFIS for DVVNL Data

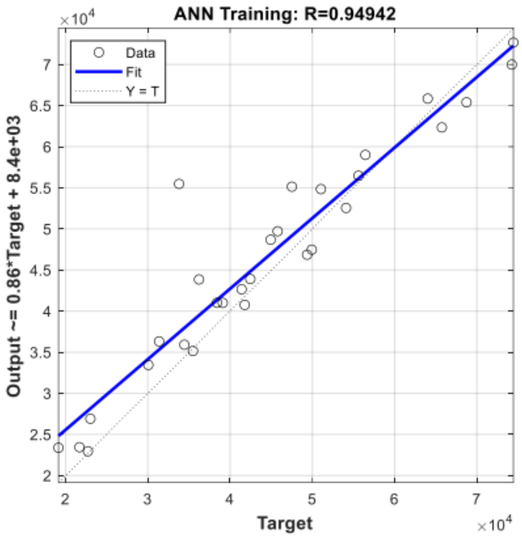

Fig. 8: Regression Plot During ANN Training (DVVNL data)

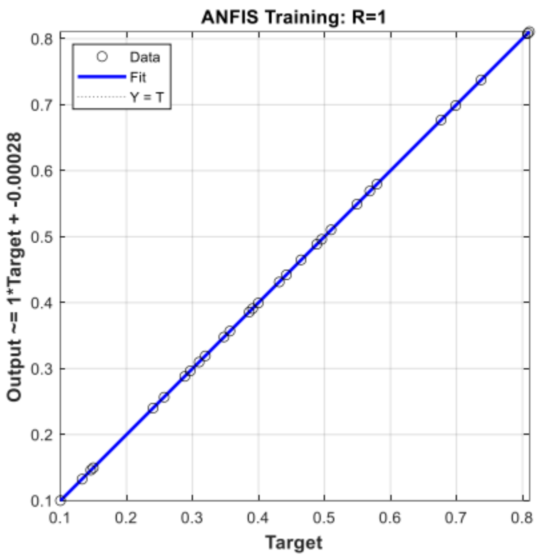

Fig. 9: Regression Plot During ANFIS Training (DVVNL)

Table 2: Training Performance - DG Set

Parameter	ANN	ANFIS
MAPE	0.33985	0.002158
MSPE	0.291084	2.70E-05

Table 3: Testing Performance - DG Set

Parameter	ANN	ANFIS
MAPE	0.379392	0.30509
MSPE	0.808069	0.147748

Table 4: Training Performance - DVVNL

Parameter	ANN	ANFIS
MAPE	0.091853	0.000454
MSPE	0.022486	2.91E-07

Table 5: Testing Performance - DVVNL

Parameter	ANN	ANFIS
MAPE	0.099902	0.049838
MSPE	0.021537	0.004334

Table 6: Training Performance - Solar

Parameter	ANN	ANFIS
MAPE	0.490265	0.001137
MSPE	0.690924	2.30E-06

Table 7: Testing Performance - Solar

Parameter	ANN	ANFIS
MAPE	0.137136	0.035488
MSPE	0.047146	0.003203

Results indicate that nontrivial nonlinearities and the fact that the ANFIS model itself stores a powerful property of every existing system known as nonlinearity make it a generic tool to both approximate and predict different systems.

6. Conclusions

This paper shows the suitability of ANFIS, in predicting electricity consumption for different power sources like solar, hydel and diesel generation. The hybrid model is proved empirically to outperform significantly traditional ANN models in accuracy of predictions. More precisely, during training and testing, the best performance of the ANFIS model was reached with MAPE as low as 0.002158 and 0.035488, respectively, whereas the best results of ANN model for the same datasets were 0.33985 and 0.137136, respectively. These measurable parameters confidently indicate the strength and efficacy of the ANFIS model to deal with complex and nonlinear energy consumption data.

The results further vindicate ANFIS as a smart grid energy prediction technique and highlight its adoptability for practical energy management systems. The model’s capability to blend fuzzy logic with neural adaptation comes in handy to tackle uncertainties and enhances the reliability of forecasts. Further work is directed towards extending and experimenting with more sophisticated hybrid architectures (e.g., LSTM-ANFIS, CNN-RNN) which are capable of temporal sequence manipulation and feature extraction. This may bring more improvement to the model's performance, especially for the long-term and high-frequency energy prediction cases.

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Cite: S. KUMAR et al., "Enhancing Electricity Consumption Forecasting using Hybrid ANN-ANFIS Models for Smart Grid Applications". Evergreen, 12 (03) 1589-1597 (2025). https://doi.org/10.5109/7388851.